SYSTEMIC RISK AND HETEROGENEOUS LEVERAGE IN BANKING NETWORKS: IMPLICATIONS FOR BANKING REGULATION

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SYSTEMIC RISK AND HETEROGENEOUS LEVERAGE IN BANKING NETWORKS: IMPLICATIONS FOR BANKING REGULATION

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Thesis Abstract

Can Sever, “Systemic Risk And Heterogeneous Leverage In Banking Networks: Implications For Banking Regulation”

In this paper, I study systemic risk implications of balance sheet heterogeneity in a banking network. More specifically, I analyse systemic impacts of financial leverage heterogeneity in a banking system under the existence of idiosyncratic shocks. It has been shown that, introducing leverage heterogeneity in the banking system strictly changes systemic risk measures and reveals the significance of bank spedicif characteristics. In the calibration, I have used the historical financial leverage data of the US banking system used in a recent stress testing exercise conducted by the FED. Through experiments, I observe that relative systemic significance of the biggest and the most connected borrowers alters depending upon connectivity of network. The evolution of the network, systemic consequences of interbank market size and market segmentation are also analysed in case of idiosyncratic shocks with different target banks. This study is also related to the recent BASEL III regulations on systemic risk and the treatment of the Global Systemically Important Banks (GSIB's). This approach can be useful to assess to what extent the recent capital surcharges on GSIB's can be useful to curb the financial fragility in the banking system. I show that, applying surcharge for the most levered banks reduces the total systemic risk existing in the banking system.

Tez Özeti

Can Sever, “Bankacılık Ağlarında Sistemik Risk Ve Heterojen Kaldıraç: Bankacılık Düzenlemesi İçin Çıkarımlar”

Bu makalenin konusu, bankaların bilanço farklılıklarından doğan sistemik risktir. Daha özel olarak, kaldıraç heterojenliğinden ileri gelen risk sonuçlarını, bireysel şoklarla ele aldım. Sonuç olarak, kaldıraç heterojenliği bankaların bireysel özelliklerinin önemini ortaya koydu ve sistemik risk ölçütlerini etkiledi. Kalibrasyonda, Amerikan bankaları için yapılan stres testini baz aldım. Deneylerde, merkezi konumda olan ve işlem hacmi büyük olan bankaların görece öneminin değiştiğini gözlemledim. Bankacılık ağının sok sonrası değişimi, market segmentasyonu ve bankalar arası para hacminin etkisini irdeledim. Bunu yaparken şok ile karsılasan bankaların karakteristiklerinin sonuçlara etkisine de baktım. Bu çalısma BASEL III düzenlemeleriyle de ilgili olup global olarak sistemik önemi olan bankaların (GSIB) tanımlanmasını amaçlamıstır. Yeni kapital gereklilikleri ve sürşarj politikalarının verimliliği de bu çalışmada mercek altındadır. Ek kapital gerekliliklerinin sonucunu analiz edip finansal dayanıklılığa bu politikanın etkisi gözlemlendi.

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CHAPTER 1

INTRODUCTION

After the global crisis in 2008, systemic risk has received a large attention both from academia and policy makers. Recent financial regulations, such as BASEL III, has given a special importance on the treatment of systemic risk. The literature on systemic risk employs different approaches. The first approach uses market prices to measure systemic risk. For instance, Acharya et al. (2010) use systemic expected shortfall (SES) as a risk indicator. Acharya et al. (2010) and Brownlees and Engle (2010) modify expected shortfall based metrics to measure systemic risk. By measuring the systemic risk, regulators may estimate how much capital is necessary in case of a systemic risk. The other approach is the use of network theory. Huang et al. (2011) study contributions of banks to systemic risk according to their default probability, institution size and asset correlation, and recommend a surcharge policy for systemically important financial institutions (SIFI's) or more recently Global Systemically Important Banks, GSIB's. Acharya et al. (2010) provide an example of liquidation costs in the systemic risk literature. Acharya and Merrouche (2010) analyse bank demand for liquidity and its effects in the interbank market during the period of crisis. One disadvantage of market based systemic research is that these methods rely on older tools used to predict risk and crisis as suggested by Danielsson et al. (2012). An alternative approach to model systemic risk is to use network measures. Following the seminal paper by Erdös-Rényi (1959) network research has become very popular. Bonancich (1987) and Borgatti (2005) are important papers for measuring centrality and systemic risk in the literature. More recently, Hu et al. (2010) and Soramäki and Cook

(2013) develop algorithms to identify systemic importances of nodes in a network. Empirical studies on interbank networks is also a popular research area. Kuzubaş et al. (2014) conducted an econometric analysis of Turkish 2001 banking crisis using various centrality measures commonly used in network theory. They employed a methodology to observe the evolution of financial network during the period of the crisis. Arnold et al. (2006) is another example which studies topology of the real network for the US market. Benitez et al. (2014) investigate the evolution of linkages for Mexican banking system and proposes non-topological risk measures. They include a comparison of payment system and interbank exposures in terms of their network structures, and show that interconnectedness of a bank is not necessarily related to its asset size. Puhr et al. (2012) investigate contagiousness for Austrian interbank market, whereas Caldarelli et al. (2007) conduct the network analysis of Italian overnight money market. Cont et al. (2010) use banking data, and analyse how balance sheet sizes and network structure affect the systemic risk contribution of the institutions. They have to-the-point policy implications targeting most contagious banks in the system. Iyer and Pedró (2010) conduct a comprehensive econometric analysis for a natural experiment, and conclude that a policy targeting the systemic risk should decrease excessive exposures to single institutions in order to limit the effects of potential shocks. Simulation based studies investigate the role of interbank linkages in absorbing or amplifying risk. Nier et al. (2007) and Montagna and Lux (2012) construct balance sheet based network models in order to investigate the link between network topology and systemic risk. Iori et al. (2006) study banking systems with both homogeneous and heterogeneous banks. Their findings suggest that interbank market stabilizes the system for homogeneous banks case, whereas its role remains ambiguous in systems with heterogeneous banks. Gai, Haldane and Kapadia (2011), using another model based approach, infer policy recommendations about the structure of network. Jo (2012) extends network analysis in Chan-Lau (2010) linking liquidity risk and solvency risk and discuss how they are related to Basel requirements. Haldane (2009) discuss the role of complexity and concentration in amplifying the risk in the system, and argue that interconnections among financial institutions may serve as shock amplifier or absorber according to the range of connectivity. Eisenberg and Noe (2001) and Diamond and Dybvig (1983) are model based network studies also including market dynamics. Eisenberg and Noe reveal the existence and uniqueness of clearance vector for financial system in a *fictitious default algorithm*, whereas Diamond and Dybvig look at the effects of bank run with associated policy issues. Although the latter creates a single bank system, it can be seen as the representative for financial intermediary industry. Gleeson et al. (2012) propose a method for calculating the expected size of contagion cascades in the network based models of Nier et al. and Gai and Kapadia (2010). Bluhm *et al.* (2013) incorporate market equilibrium in a heterogeneous banking network focusing on the microfoundations side including optimal portfolio decisions along with liquidity and capital constraints. Many of the network research on banking assume a homogeneous balance sheet. In other words, despite a large body on the linkages between the leverage and systemic risk, many of the existing network models have been built on homogeneous leverages. For instance, Adrian and Shin (2010), Adrian and Shin (2008), Danielsson et al. (2012), Brunnermeier (2009) reveal the importance of financial leverage in understanding systemic risk. Acharya and Thakor (2010) are based on the general idea that risk is not internalized by an institution when deciding on its own optimal leverage level. They also focus on the conflicting effects of leverage: enhancing liquidation and increased risk for the system. They have two crucial features. First, leverage is procyclical, that is, it is high when balance sheet size is large. Second, both the balance sheet size and leverage are determined by the riskiness of the institution. Thurner (2011) provides an analysis on the effect of leverage levels. By simulating related conditions for dynamic agent based models, he tracks the effect of excessive leverage on the systemic risk, and shows that higher leverage gives rise to higher volatility in prices in the financial markets, hence higher risk. Moreover, small random events which are harmless for low levels of leverage affects the system severely in the case of relatively high leverage. Brunnermeier and Sannikov (2012) propose a macroeconomic model and investigate how risk sharing mechanisms affect the level of systemic risk. They argue that a risk sharing mechanism for an idiosyncratic shock makes institutions less financially constrained and gives them incentive to take high leverage positions which result in a more unstable system. On the other hand, Pais and Stork (2013) use Extreme Value Theorem to estimate the effect of short positions of institutions for France, Italy and Spain. They show that there is a positive correlation between short-selling and systemic risk, and argue that higher leverage levels (or lower capital adequacy ratios for banks) are more likely to correspond with higher short positions. Ryoo and Kim (2012) introduce systemic leverage indicator which is a signal for financial distress and also a measure for systemic risk accumulated for Korean banks. Ramadan (2012), employing cross-sectional data analysis, concludes that leverage is a significant factor for risk no matter which method is used for estimating the leverage levels. In an interbank network, financial institutions establish lending and borrowing relations based on their balance sheets. An idiosyncratic shock hitting a bank in the system may spread over the entire system via these linkages. Thus, interbank relations are an important channel through which contagion occurs. As a result, idiosyncratic risks of banks may impair the stability of the whole system (i.e. individual risks of banks may contribute to system-wide risk depending upon their balance sheet and network positions.). Resilience of the system is measured by the amount of the contagion which determines the system-wide effect of the shock. Moreover, banks with high leverage values participate in more lending activities in the market. Balance sheet and network positions of banks and the connectivity of the network are both crucial aspects of financial stability. Therefore a model for banking system should incorporate these features. In this paper, I introduce a balance sheet based network model of asset shocks with heterogeneous leverage levels, which is missing in the previous literature. To the best of my knowledge, this paper is the first attempt to fill this gap.[1] We calibrate leverages across banks using data from Federal Reserve (2012). In the case of varying degrees of leverages among banks, I create a stress scenario via the spread of an idiosyncratic shock. By performing simulations in Monte Carlo framework with geometric network, I focus on the effects of connectivity of the network, volume of interbank transactions, shock size, leverage distribution and liquidity on stability. I also investigate the decrease in the connectivity at the end of the shock spread process. We show that results are significantly different than the case with homogeneously leveraged banks. Additionally, I identify banks that are affected depending on their initial position in interbank lending-borrowing relations. In the model, even the net borrowers are more open to first step shocks, net lenders are more sensitive to losses due to counterparty defaults. I investigate the impact of connectivity on the relative resilience of the net borrowers and lenders with these competing forces. In this analysis, in addition to the number of defaults, we also propose various measures of systemic risk. First, I investigate the number of banks whose net worths fall below capital adequacy ratio (CAR). That is, banks deplete their required minimum capital which is 8% after the shock. This measure is more complete and sensitive compared to the the number of defaults, since the number of banks whose net worths fall below CAR limit allows us to observe all banks which are significantly

[1] Similar analysis of systemic risk is conducted in Nier et al. (2007), but the model they propose does not capture the impacts of heterogeneous leverage across banks. They do not incorporate any relation between size of bank specific interbank transactions and leverage levels.

affected. I introduce different target banks for the idiosyncratic shocks (the biggest borrower, the smallest borrower, random bank and the most connected borrower) for different experiments and also keep track of the relative significance of these for the banking network in cas of idiosyncratic shocks. I also study the impact of the variance of leverage distribution, homogeneous leverages and the case of two extreme banks with low and high leverages while overall mean of the leverage is constant. Moreover, while looking at the impact of variance of the leverage sequence, I compute the Gini coefficient (calculated by % depletion of banks' net worths) where higher Gini coefficient implies that more banks are affected severely losing significant portions of their net worths. Total net woth loss calculated as the sum of individual percentage losses are also evaluated in order to measure the systemic impacts of shocks. Based on these measures, I show that bank identity and dispersion of leverage sequence significantly affect the stability of the system for each experiments. Finally, I analyse how the results differ when we add a liquidity effect which reduces the total value of assets in the case of default in the system. This amplifies the effect of shock, especially if a highly leveraged bank is target. I provide policy implications about capital requirements, regulation of overall leverage distribution and surcharges for highly leveraged banks, and discuss how these are related to identifying SIFI's, Basel-III regulations and detection of globally systemically important banks (GSIB's). In chapter 2, I first introduce the model and define environment. In chapter 3, simulation, results and following policy implications are illustrated and discussed. Finally, chapter 4 concludes.

CHAPTER 2

THEORETICAL FRAMEWORK

I introduce a balance sheet based network model of systemic risk following idiosyncratic shocks to the asset sides. I construct an interbank money market network with N institutions. I establish a simple version of balance sheet as in Table 1.

Table 1: Balance Sheet Representation

Assets (A_i)	Liabilities (L_i)
External Assets (${A_i}^E$)	Unsecured interbank borrowing (${L_i}^I$)
Unsecured interbank lending (${A_i}^I$)	Equity (E_i)
	External deposits (${L_i}^E$)

Balance sheet identity of bank i is given by

$$A_i^E + A_i^I = L_i^I + L_i^E + E_i \ \forall i = 1...N. \tag{1}$$

where ${A_i}^E$ are assets from outside of the interbank market. It consists of collaterals, liquid assets, fixed assets and other long term lending activities. External deposits are liabilities to external depositors. θ_i is defined as liability composition of bank i:

$$\theta_i = \frac{{L_i}^E}{L_i} \tag{2}$$

Having constructed θ_i measure, I have the chance to capture a relationship between leverage and interbank lending values of banks.[2] Total assets is defined as γ_i times equity for each bank: $A_i = \gamma_i E_i$. Since, leverage of a bank is the ratio of total assets to the equity (net worth),[3] γ_i is the leverage for bank i, and γ_{Nx1} is the leverage vector for the system.

The model aims to capture the effect of varying leverages in an otherwise homogeneous banking system, thus I assume uniform balance sheet sizes across banks. I also introduce the symmetry of liability compositions of banks in terms of external deposits via identical θ values. I also establish a negative relation between interbank borrowing and equity of a bank in the following way:

$$L_i{}^I + E_i = (1 - \theta_i)L_i \quad \forall i = 1...N. \tag{3}$$

where θ_i and L_i values are same for all banks. In this regard, if a bank has higher leverage value (thus lower capital), it will participate in more interbank borrowing. It will become a bigger borrower for the market than an average bank. A direct implication of equation (3) with identical (θ, L) pair with $A_i = \gamma_i E_i$ is that highly leveraged banks need to borrow more in the interbank market. Consequently, despite homogeneous sizes, asset compositions are different within banks. Given the structure of the interbank network, A_i, θ_i and γ_{Nx1}; E_i, $L_i{}^I$, $A_i{}^E$ and $A_i{}^I$ are determined endogenously. I distribute by interbank borrowing uniformly among lending links of any bank[4]. Thus, a bank having high leverage is more likely to be a net borrower in its balance sheet position, i.e. the bank that borrows the highest amount in the system is the one with the highest leverage. I introduce balance sheet heterogeneity by allowing γ values differ across banks with same balance sheet sizes, where different γ_i's imply heterogeneous leverage levels, and thus net

[2]See equation 3.

[3]See Adrian and Shin (2010).

[4]As in Gai, Haldane and Kapadia (2011), $\sum_{i=1}^{N} A_i^I = \sum_{i=1}^{N} L_i^I$ in interbank market.

worth values for the banks. Banks with low net worth, i.e. a lower equity buffer to absorb adverse shocks, are more sensitive to financial shocks and they also transmit higher portions of the financial shocks to the creditors, since I limit the potential transmittable shock with the size of bilateral interbank claims. That is, they are more prone to default by first step shocks because of low capital buffers. Second, since they are big borrowers for the system, they have a larger capacity to transmit more amount of shock to their creditor via interbank claims that they are not able to pay when they default. On the other hand, banks with high capital will be stronger against adverse financial shocks. To specify the bottom line of this model, introducing heterogeneous leverages levels and equation (3) give rise to have some big lenders and also some big borrowers in the network via this kind of initial market segmentation. The banks having high leverage (low capital) are bigger borrowers of the system, and vice versa. Leverage levels are calibrated using data for a sample of US banks.[5]

2.1. Shock Transmission

I introduce idiosyncratic shocks received by the asset sides of different targets. A shock (s_i) that wipes out some fraction (k) of the assets of bank i in the interbank money market,[6] $s_i = k \cdot A_i$. Random banks and targeted banks receive shocks in different experiments. In order to investigate 'too big to fail' and 'too connected to fail' arguments, I target most connected and the biggest borrowers of the system. Since the shock spread from borrower to lender via unpaid interbank claims, the most connected and the biggest borrowers are expected to be systemically

[5] Comprehensive Capital Analysis and Review 2012: Methodology and Results for Stress Scenario Projections (March 13, 2012) by Board of Governor of the Federal Reserve System contains 19 banks. I simulate 25-bank system. It is reasonable by considering the evidence represented in Leaven, Ratnovski and Tong (2014). In section 3, I mention the calibration process in detail.

[6] Note that shock size is k means k fraction of assets of that bank is wiped out.

important. I investigate the effect of connectivity in their relative systemic significance. In addition, to see the impact of balance sheet position on the systemic significance of a bank, I also target the smallest borrower in the system. Since initial shock spreads through bilateral exposures among banks, if net worth of a bank (E_i) is not sufficient to absorb the shock, bank defaults and residual shock is transmitted to the lenders of that bank. I define an event for bank i as default if below constraint is breached:

$$A_i^E + A_i^I - L_i^I - L_i - s_i > 0 \tag{4}$$

where s_i is idiosyncratic shock to assets of the bank. In case interbank liabilities are still not sufficient to absorb the residual shock, some of the losses are born by depositors outside of the system. A default borrower cannot pass an amount greater than its debt to a lender. By equation (5), if $s_i < E_i$, bank does not default but its net worth becomes $E_i' = (E_i - s_i)$, which implies even in the case of no default, the bank becomes weaker through the shock spread process. Thus, it is more vulnerable for the potential shocks arising from counterparty defaults during future rounds of the same process triggered by initial shock. If $s_i \geq E_i$, bank defaults and cannot pay its interbank debt. In the model, highly levered are more vulnerable to the first step shocks due to low equity buffer, and through the procedure, since they borrow large volumes, they have a larger capacity to pass the residual shock to lender. As a second source of vulnerability, although they have higher capital values, bigger lenders and are more open to lose their interbank assets in big amounts. Thus connectivity plays a role in relative significance of net lenders and borrowers for the rest of the system. In the case of default, the shock that is not absorbed potentially transmitted through interbank borrowing links of the default bank is $(s_i - E_i)$. If $(s_i - E_i) < {L_i}^I$, creditor banks receives a total shock of $(s_i - E_i)$. If $(s_i - E_i) > {L_i}^I$, the whole amount cannot be transmitted, then transmitted shock is ${L_i}^I$. Thus, a bigger borrower potentially inherited more amount of shock to the counterparties. Transmitted shock is divided among lenders proportional to the lending amounts. The shock transmitted to bank u is calculated as the ratio bank i's total borrowing to the number of its lenders, which is given as:[7].

$$s_u = \frac{s_{i(t)}}{H_i}$$

where H_i is the number of lenders of bank i and $s_{i(t)}$ is the transmitted shock to the lenders after the defaults of bank i. $s_{i(t)}$ is defined as

$$s_{i(t)} = \begin{cases} {L_i}^I, & \text{if } (s_i - E_i) > {L_i}^I \\ s_i - E_i, & \text{otherwise} \end{cases}$$

Following the benchmark procedure, *sequence of defaults* in Eisenberg and Noe (2001) is used for modelling the domino effects. After this first transmission, if the creditor bank have a net worth enough to absorb shock, $s_u < E_u$, it withstands the shock and its net worth becomes $E'_u = (E_u - s_u)$. If shock is not absorbed, $s_u \geq E_u$, it is transmitted by the same mechanism and rounds continue until no further defaults occurs. The possible terminal points of this scenario are the failure of the whole system where no bank left to transmit the remaining shock, or no further defaults occur since the whole shock is absorbed by banks through linkages.

[7]While distributing the residual shock among the creditors of the default bank, I modify the weighting algorithm of *proportionality* principle of Eisenberg and Noe which is based on the weights of the borrowing links between banks. Defining a *relative liability matrix*, they introduce distinct weights of lenders in the total lending of default bank. As a result, if a default occurs, all claimant nodes are paid by the defaulting node in proportional to the size of their claim of the bank assets. On the contrary, I do not introduce different weights for borrowing linkages. It has a direct result in distributing the residual shock equally among creditors in this framework. In the benchmark model, because all lendings are given equally, if there are m lenders of default bank, each lender receives $\frac{s_i}{m}$.

2.2. Methodology

In this chapter, I illustrate the simulation procedure. Exogenous parameters of the system are number of banks (N), leverage (γ_{Nx1}) vector, fraction of external deposits to total liabilities (θ) and total assets (A). Benchmark parameters are represented in Table 2. Given the exogenous elements of balance sheet, I first determine components that are independent from the network. Finally, I create realisations of an unweighted geometric network,[8] and construct ${A_i}^I$ (and ${A_i}^E$) values endogenously. Links are not netted .[9] Each round in the simulation procedure represents a time period. In round 1, an exogenous and idiosyncratic shock hits bank i, and after a potential default, $s_{i(t)}$ is transmitted to the lenders of bank i. Round 2 captures the effect on the lenders of bank i through the transmission process. Rounds continue until no further defaults occur or all banks in the system default. In addition, I consider all claims among banks are insecure, no collateral, and there is no external intervention mechanism.

[8]Studies using real world network infer that a few institutions have large number of links, as discussed in Gai, Haldane and Kapadia (2011), geometric network is more appropriate for real world structures. The only randomness in the model stems from this network structure. It maps to the randomness of assets side of banks via interbank lending of banks. In order to eliminate noise and differences in realisations, I create Monte Carlo framework over 1000 runs of the system with 1000 network realisations, and we take average values across realizations of random graph. I follow the assumption used in Nier et al., May and Arinaminpathy (2010) and Montagna and Lux (2013), and assume that shock propagation is too fast for banks to revise their links and positions.

[9]That is, both ij and ji entries of the adjacency matrix can be 1 at the same realisation of the network. If bank i both lends to bank j and borrows money from bank j, shock may spread from j to i, and from i to j. As a convention ji link represents j lends to i. In below graphs, "Average degree" is the average of in-degrees and out-degrees for each bank, i.e. average number of banks that any bank is connected to.

Table 2: Summary of Benchmark Parameters

Parameter	Benchmark value	Range of variation
A	125000	Fixed
N	25	Fixed
θ	0.75	0.6-0.85
k	0.4	0-1
γ_{Nx1}	CCAR, 2012	0-2σ_γ

CHAPTER 3

SIMULATIONS AND RESULTS

In this chapter, I illustrate and discuss the results. I conduct simulations for a 25-bank system.[10] with heterogeneous leverage levels.[11] I calibrate leverages of banks using data by Board of Governor of the Federal Reserve System.[12] As a result of ascending leverage ordering of banks in the system, I note that Bank 25 is the biggest borrower.[13] Figure 1 illustrates the adopted sequence for leverages.

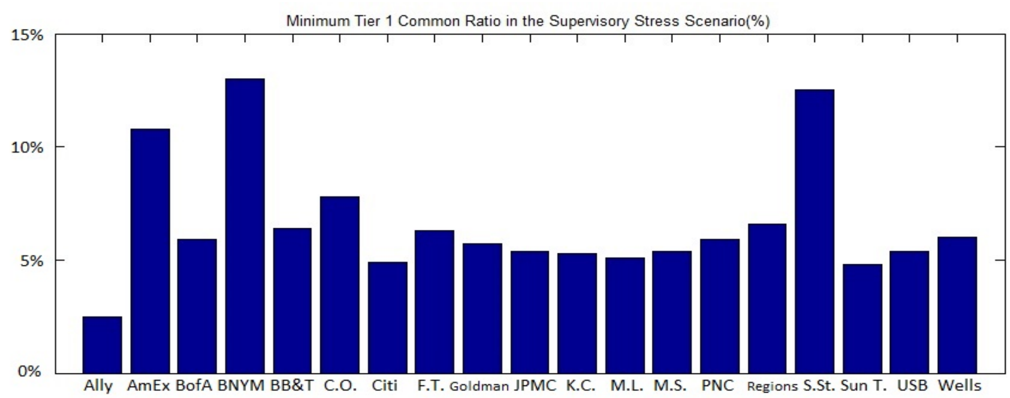


Fig. 1: Leverage sequence

[10]Banks in the system are sorted in an ascending order according to their leverages. That is, 1^{th} bank is the one with the least leverage (i.e. smallest borrower) and 25^{th} bank is the most leveraged one (i.e. the biggest borrower)

[11]19 bank holding companies were required to participate CCAR 2012. Hence, I need to add 6 banks to this leverage sequence. I follow a procedure according to the mean and standard deviation of data. I add 4 banks as +/- one standard deviation, and 2 banks at the mean.

[12]See CCAR, 2012 for the BHC's.

[13]It can be also interpreted as different financial sectors with distinct levels of leverages, and interact each others via lending and borrowing.

I calculate the average number of defaults and introduce a new systemic risk measure which is the number of banks falling below CAR, that is %92 of the net worth.[14] I also porpose 'systemic net worth loss' in the system as a measure of systemic risk. It is defined as the total loss in equities of banks in percentages. Finally, by depletion of individual equities, I calculate 'Gini coefficient of shock spread process' as a risk indicator. The results demonstrate the importance of heterogeneous leverages compared to a banking system with homogeneous leverage. Systemic significances of the biggest and the most connected borrowers alter depending upon initial shock size and average connectivity of the network. The two competing forces that give rise to this results are the impacts of total amount that has been borrowed and number of banks that can be affected following the default of the borrower. For different connectivity levels and shock sizes, these dynamics of systemic risk dominate each others and leads to change in relative importances of the two players in the network. In terms of borrowing amounts, I study too big to fail and too connected to fail arguments.As well as altering significance of the biggest and the most connected borrowers, in case that the most connected one faces the shock, network connectivity shows "knife-edge" characteristics as discussed in Haldane (2009). On the other side, when the biggest borrower is hit, links act as shock amplifier up to a threshold level, then they simply act as shock absorber. By comparing the cases in which the biggest and smallest borrowers receive the shock, I also observe that the amount of interbank borrowings of the bank that faces the shock changes the risk inherited to the system. I introduce a measure of systemic risk, 'number of banks below CAR', which is found to be a

[14]Note that, in the graphs for the number of defaults and the number of banks below CAR, 0 means no defaults, and 1 means that only shocked bank itself defaults. It is natural that there is threshold in the shock to make shocked bank default. That is, up to a point, small shock sizes cannot make any banks default, but after a threshold, these measures jump from 0 to 1 meaning that bank itself defaults or falls below CAR. In case there is further defaults more than 1, I take average number of defaults over realisations of network.

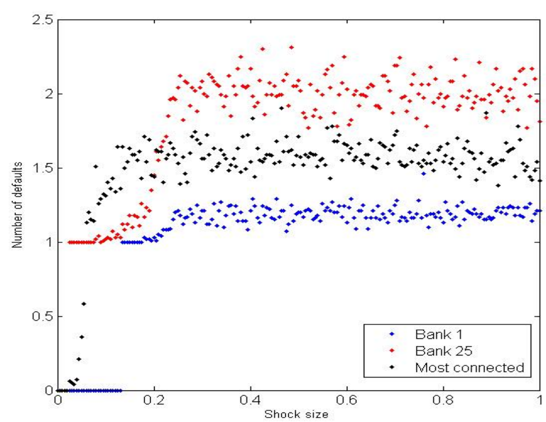
leading indicator of the measure number of defaults for increasing size of shocks. As initial shock size increases, average connectivity of network lowers when compared with the initial levels. Due to potentially higher number of defaults (i.e. unpaid claims), there are more links to be broken for higher level of shocks. Initial net balance sheet positions of banks that receive the shock affect systemic significance of bank. Depending upon average connectivity of network, for same shocks, systemic significance of initially net lender and borrowers alter. Similar to above discussion, there are two competing forces which give rise to this result. The net lenders are more open to net worth losses due to potential defaults of their borrowers. On the other side, net borrowers are more vulnerable to shock due to low equity buffers. These dominate each others for different levels of connectivity. As average volume of interbank transactions decreases, system is more resilient to the shocks. Since the biggest borrower stays in the upper limit of interbank borrowing, the effect of this volume is most clear for the biggest borrower. For identical leverage levels, when system-wide leverage increases, systemic risk increases.[15] More interestingly, in case of homogeneous leverages, I observethe behavior of inherited risk significantly differs for scenarios in which a random bank and the most connected bank receives the trigger shock. Fitting a distribution to leverage sequence, I observe the effect of leverage dispersion among banks on systemic risk in case of same levels of average leverage. I create different scenarios like homogeneous leverages, increasing standard deviation of sequence (i.e. more disperse leverage levels) and a case in which I have 2 extremely low and high levered banks (i.e. 23 homogebeous banks at the mean leverage value). I propose new measures of systemic risk in order to see how the system is affected more asymmetrically and severely: 'Gini coefficient of shock spread process' and 'systemic net worth loss'. I observe consistent results with these measures. I note

[15] This result is also illustrated in Nier et al. (2007).

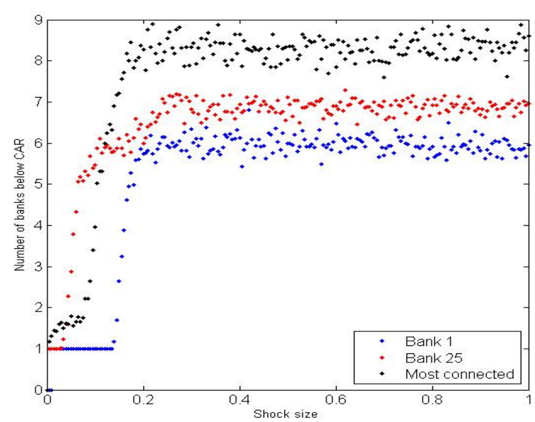
that increasing leverage dispersion within banks makes the system less resilient especially if the biggest borrower faces the shock. Also using the case of leverage sequence with 2 extremes, I verify previous result with taking a random bank, the biggest and the most connected borrowers as target of the shock. I model the liquidity effect similar to Nier et al. (2007). I note that the impact of liquidity channel is more obvious in case of a shock to the biggest borrower. I examine effectiveness of surcharge policy in 3 different scenarios: the biggest, the most connected and the smallest borrowers as target of idiosyncratic shocks. I compare same amount of capital injections with a uniform increase in equities and a surcharge to the 5 mostly levered banks. Excluding the shock to the smallest borrowers, I observe the effectiveness of surcharge policy when compared with uniform capital injection using same level of total capital.

3.1. Effect of Shock Size

Figure 2(a) illustrates the consequences of increasing shock size (k) in terms of defaults. For smaller sizes, the most levered bank (i.e. the biggest borrower) is immediately affected. It starts to contaminate the residual shock to the rest of the system for even very tiny shocks. On the other hand, even the most connected lender does not necessarily default for smaller shocks, as soon as it defaults, it spreads the residual shock to a large number of banks. That is why it inherits more risk to the system than the biggest borrower for shock levels around 0.1. The least levered (i.e. the smallest borrower) bank does not lose its net worth completely for relavitely larger shocks. Even after it defaults, since it has the least capacity to transmit shock (due to less amount of borrowing), when a shock hits Bank 1, the consequences are better when compared with other targets. There is another tipping point of shock around 0.2. Since the most connected bank spreads it among many banks, its effect is severe up to this point. On the other hand, after this threshold, since the biggest borrower have the maximum capacity to transmit shock (due to large borrowing amounts), the volume effect for the biggest borrower dominates the interconnectedness effect for the most connected one. Hence, for larger shock levels, the biggest borrower makes system more vulnerable. Hence, I observe that systemic significance of too big and too connected borrowers change depending upon shock size. I also note that after shock levels around 0.3, since the volume of transaction in interbank market limits the potentially transmitted amount, the rest of shock is born by outside depositors and the effect of shock stabilizes.



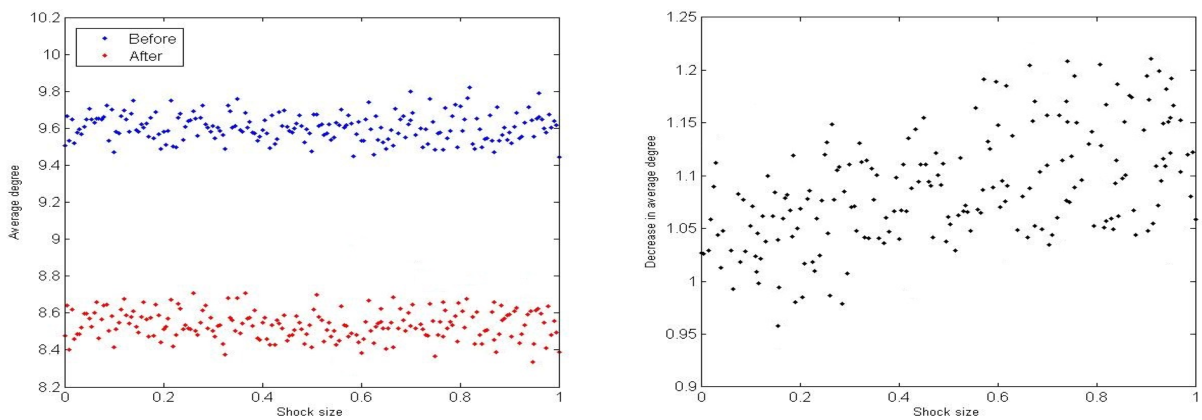
((a)) Defaults



((b)) Banks below CAR

Fig. 2: Effect of shock size

Figure 2(b) is the number of banks which already go below their CAR. For this measure, since shock contaminates many lenders via the most interconnectedness one, after a tipping point around 0.1, it is the one which may affect the most number of banks in the system. In contrast to number of defaults, size effect cannot dominate interconnectedness effect in this case. I also observe that it is a leading indicator of number of defaults. For instance, around a shock level 0.2, many banks already fall below the critical limit, whereas there are few banks to default. For low levels of shock, this more complete measure allow to see the banks which are more vulnerable and more prone to default with possible larger shock. Thus, it is significant to monitor the equity levels of banks in the period of stress in order to keep track of banks that become vulnerable and to foresee the potential defaults n case of continuously rising stress in the banking network. I also analyse the decrease in the connectivity of the banking system with idiosyncratic shock. Due to default banks, interbank claims may not be paid and borrowing links may be broken. Figure 3 illustrate the result. I observe a decrease in average degree in the network. As shock size increases, more banks face default and more links on average are open to be broken due to unpaid debts.

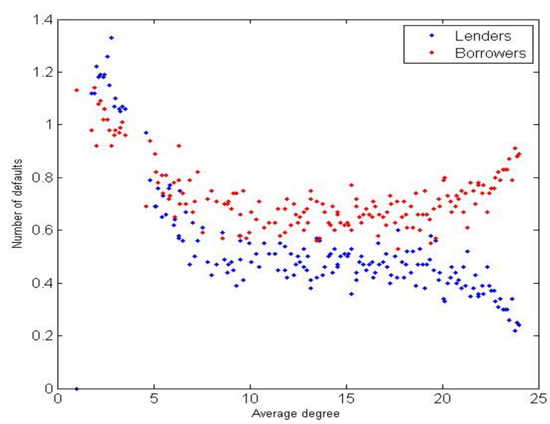


((a)) Average degrees ((b)) Decrease in average degree

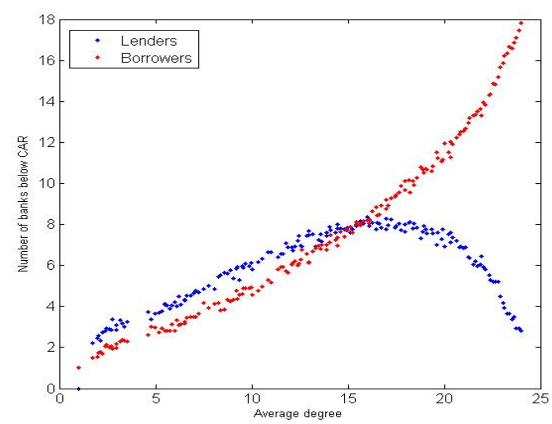
Fig. 3: The most connected bank

3.2. Effect of Initial Balance Sheet Positions

I analyse the effect of balance sheet position on the strength and systemic significance of individual banks. I aim to identify the banks that are potentially weaker due to market segmentation in interbank exposures. In an interbank market, there are net borrowers and lenders initially (i.e. market segmentation). I determine initial positions of banks endogenously via network. In the model, there are 2 competing forces depending on balance sheet of banks in case of a shock. In the system, net lenders are smaller borrowers, but they have higher capital. Since they have higher E_i values, they are more resilient to first step shock. On the contrary, since they lend huge amounts, they are more open to shocks potentially arising from the borrowers. The reserve argument is valid for the net borrowers. Although they are more prone to default with first hand shocks, since they do not lend large amounts, they are unlikely to lose interbank assets arising from counterparty defaults. I see the effect of connectivity on these competing forces, and thus the effect of initial positions of banks on the financial health. In order to eliminate the first shock bias from the measures, I give the idiosyncratic shocks to random banks and take averages. Figure 4 illustrates the result.



((a)) Defaults



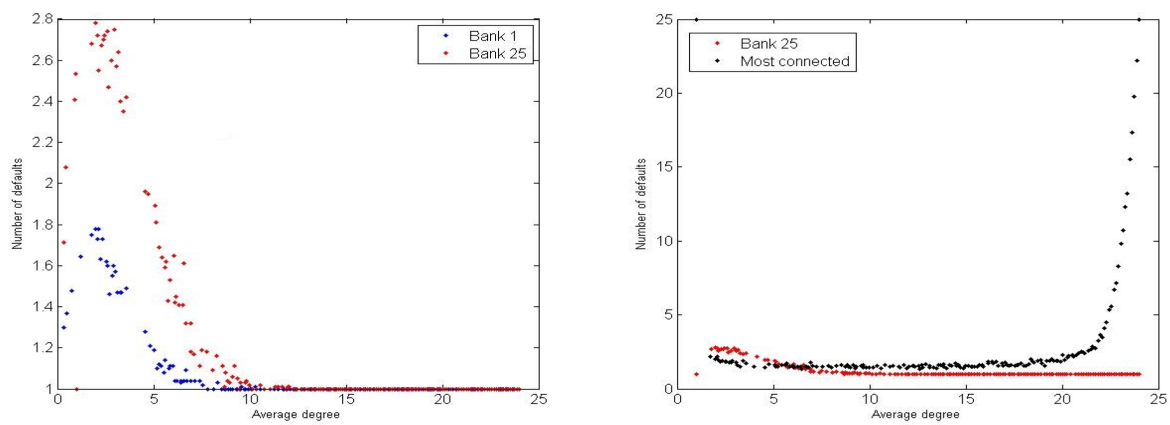
((b)) Banks below CAR

Fig. 4: Effect of initial net balance sheet positions

I observe that lenders are more vulnerable for low level of connectivity. Although they have higher capital buffers, since the shocks from borrowers are not distributed enough, the size effect for interbank claims overcomes the impact of high capital. They are affected more severely than borrowers by losses arising from counterparty defaults via unpaid claims. As interconnectedness increases, since lenders distribute total amount of lending among many borrowers, the losses coming from defaults of some borrowers do not affect them due to their high E_i value. Thus, higher capital dominates the risk depending interbank market assets. Even if one of more counterparties default, a lender do not lose too much effect due to high connectivity, hence its euqity buffer is enough to sustain solvency constraint. For highly connected networks, the gap is even higher and impact of interconnectedness is observed more clearly. The intuition is valid for number of banks below CAR, too. On the other hand, the threshold for these forces to dominate each others is higher in this case, around average degree of 15. Moreover, after this turning point, the gap in the strength of two types of banks is more clear with this measure.

3.3. Effect of Connectivity

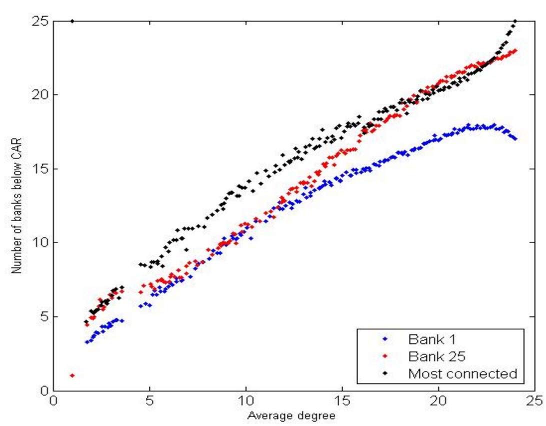
In this part, I aim to observe the systemic impacts of connectivity in case of different characteristics of targeted banks. Figure 5 and 6 represent the results.



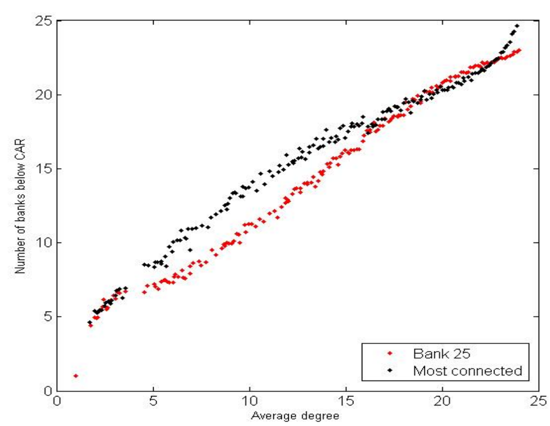
((a)) Defaults ((b)) Defaults

Fig. 5: Effect of connectivity

Figure 5 reveals the relevance of the identity of banks which receives the first shock. Figure 5(a) illustrates that a bank with the least leverage inherits large amount of risk to the rest of the system when compared with the bank with lowest leverage. The sources of higher inherited risk are low capital, high ${L_i}^I$, thus high shock transmission potential of Bank 25. The gap is persistent for a wide range of connectivity level. After a threshold where interconnectedness acts as risk sharing pool, network starts to absorb losses in both cases. Moreover, I observe the effect of connectivity on relative systemic significances of the most connected and the biggest borrowers. In Figure 5(b), if network is less connected, the biggest borrower (i.e. the most levered) is the systemically important one. It causes more banks to default than the most connected borrower. Since it transmits more amount of shock, it makes banks default in the second round. In contrast, after a connectivity around 6, the connectedness of the borrower overcomes the size effect. Thus, the most interconnected borrower spreads the shock more, and affects system severely. Moreover, it shows the "knife-edge" property of high connectivity. As discussed in Haldane (2009), after a level of connectivity, links amplify the shock for the most connected bank.



((a)) Banks below CAR



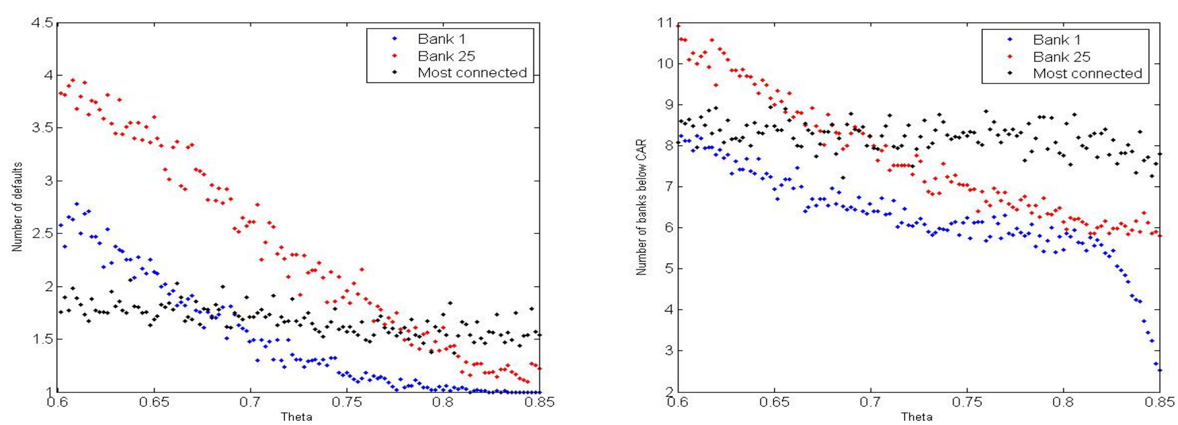
((b)) Banks below CAR

Fig. 6: Effect of connectivity

Figure 6 represents the result with the number of banks below CAR. Since the most connected bank potentially contaminates the shock to the hghest number of borrowers, it causes many banks to lose some portions of their net worths for a large range of connectivity. On the other side, there are tipping points of connectivity in terms of effects of the most connected and biggest lenders like the threshold of the number of defaults. For very low and high connectivity levels, the biggest lender affects more banks. Another result is that the smallest lender (i.e. lowest leverage) has the minimum systemic impact for all levels of connectivity, but after a connectivity level around 15, it is even less important for the rest of the system due to highly diversified bilateral claims.

3.4. Effect of Interbank Market Size

I change the size of interbank market and observe the effect of it on systemic risk in case of the biggest, the smallest and the most connected banks receive the shock. Due to equation (5), keeping net worths at the original level, as θ increases, the total amount of interbank borrowing (hence interbank lending) decreases. Figure 7 illustrates how the system is affected by the changes in the volume of interbank market.



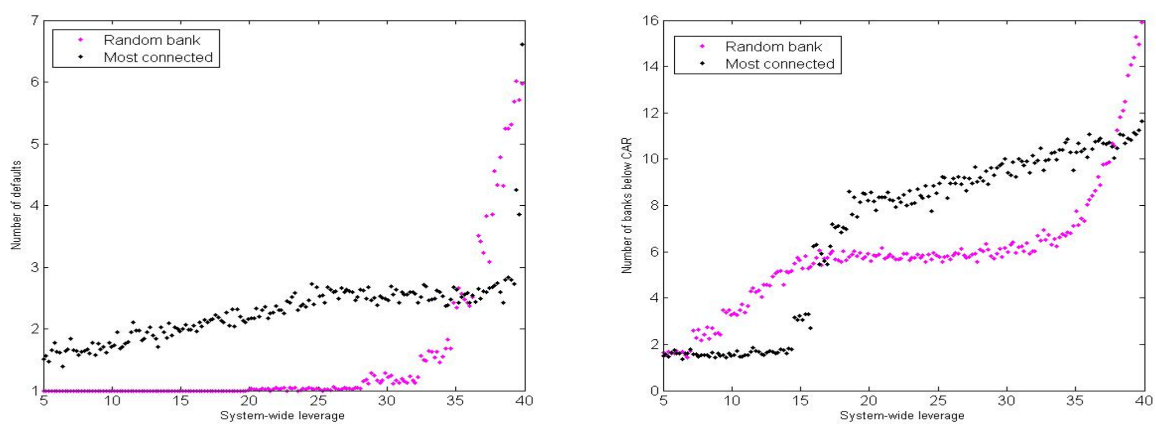
((a)) Defaults ((b)) Banks below CAR

Fig. 7: Effect of ${L_i}^I$

In Figure 7(a), as θ increase (i.e. size of interbank claims decreases), system becomes more resilient since transmittable shock reduces. The reduction of defaults is the clearest when Bank 25 receives the shock. Since it is the bank which can potentially transmit the highest amount, decreasing its interbank claims has the largest impact for the rest of the system.

3.5. Effect of System-wide Leverage

I first take leverage values equal to the mean of the leverage distribution, which corresponds to the homogeneous system. Since all banks are homogeneous and I want to eliminate noise from differences of network positions of banks that is hit, I shock a random bank in each case and take averages. In addition, in order to observe the trend of measures with increasing leverage in case of a shock the most connected lender, I also choose that bank, and give shock to it. Figure 8 represents the results.



((a)) Defaults ((b)) Banks below CAR

Fig. 8: Effect of system-wide leverage

The most connected bank spreads shock even for lower leverage levels, whereas defaults do not increase up to a level of 28 in case of random shock. I also note that number of defaults are high when a random bank receives a shock for high leverage values. The intuition behind this is that shock transmitted is higher for high leverages (since capital is low), but risk distributing role with most connected lender dominates this size effect. On the other side, there are again turning points in the significance of these two banks in terms of number of banks that are below CAR.

3.6. Fitting the Leverage Distribution

In this part, I fit a distribution to the empirical leverage sequence. Normal distribution provides a reasonable fit.[16] Parameter estimates for the fitted distribution are presented in Table 3 and empirical along with the theoretical distribution is given in Figure 9.

Table 3: Parameter Statistics for Estimated Distribution

Parameter	Estimate	Standard error
mu (μ)	17.6763	0.25655
sigma (σ)	4.6250	0.18182

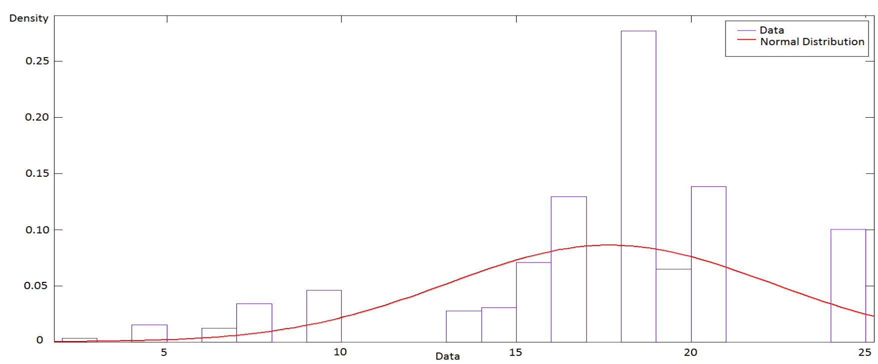
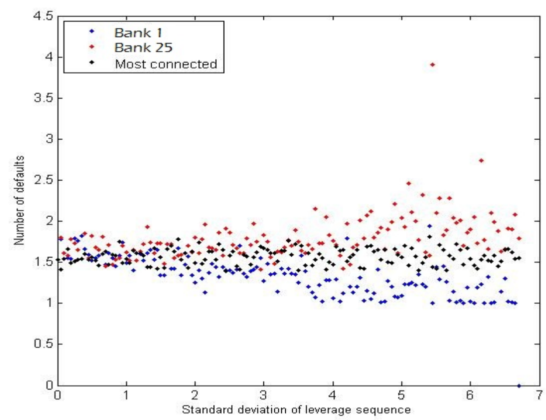


Fig. 9: Data and parametric density

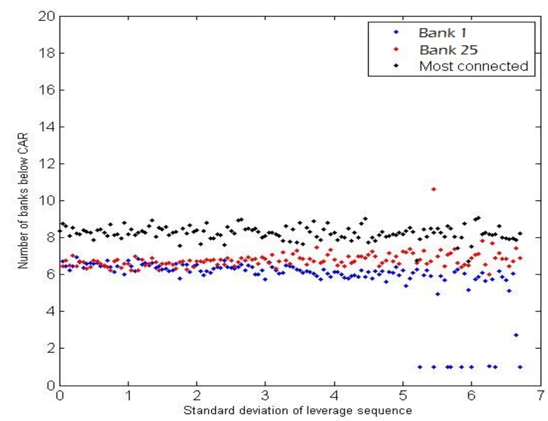
[16]Comparing log likelihood values for different distributions, I choose normal distribution which gives a reasonable loglikelihood value among other distributions, like Beta, Binomial, Extreme Value, Gamma, Pareto, Lognormal, Poisson.

3.7. Sensitivity of Systemic Risk to Leverage Dispersion

Using the estimated μ value, I illustrate the effect of a mean-preserving spread of the leverage distribution. While standard deviation of leverage sequence is increasing, since strongest banks becomes even stronger with a relatively lower leverage, a shock hitting the strongest bank has a lower effect. On the other hand, if shock hits the most leveraged bank, its systemic impact becomes more significant, since the peak of leverage sequence increases, thus net worth of that bank decreases and its capacity to pass greater residual shock increases. I observe no significant difference in the impacts of the most connected banks as leverages become more asymmetric. In addition, I do not observe a remarkable change in the number of banks that fall below CAR.



((a)) Defaults



((b)) Banks below CAR

Fig. 10: Effect of leverage dispersion

I also calculate the Gini coefficient for the spread of shock for each value of standard deviation. This allow us to measure how unequally the shock propagates through the system. It is calculated in terms of melted percentages of net worth. Asymmetry of spread of the shock is thus crucial, because a higher level of asymmetry implies more banks are affected significantly. A higher Gini coefficient means that more banks lose remarkable percentages of their net worth. In Figure 11, as variance of leverage sequence increases, a higher number of banks are affected, hence leverage dispersion in the banking system is another important measure for regulators. I note that although shock spread more asymmetrically for all cases, the risk inherited by the biggest borrower is the largest.

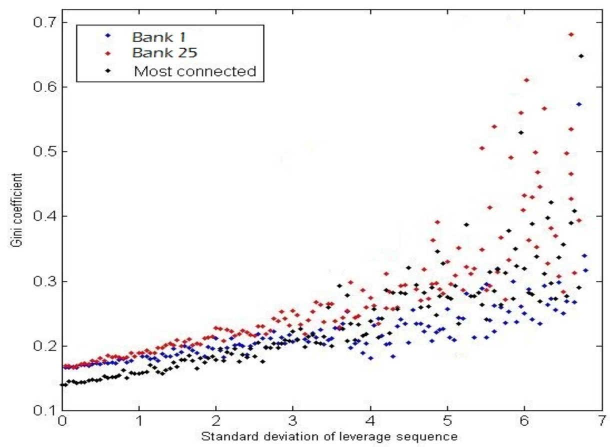


Fig. 11: Gini coefficient of shock spread process

Moreover, I introduce a new systemic risk measure: Systemic net worth loss (in %). I sum % losses in net worths of each banks. The greater this measure, the more banks affected severely. When the least levered bank (i.e. biggest borrower) receives the shock, I observe that the sum of percentage net worth losses of banks increase, as leverage dispersion increases. Although the trend is not that upward, the same kind of effect is present when the most connected borrower is hit. On the other side, since the smallest lender becomes even smaller when standard deviation increases (as its leverage decreases and net worth increases), its systemic impact is lesser. The result is consistent with Figure 11. I also note that, despite the fact that systemic net worth loss in total dereases in case of a shock to the smallest borrower, the asymmetry of loss among banks increases (which is illustrated in Figure 11).

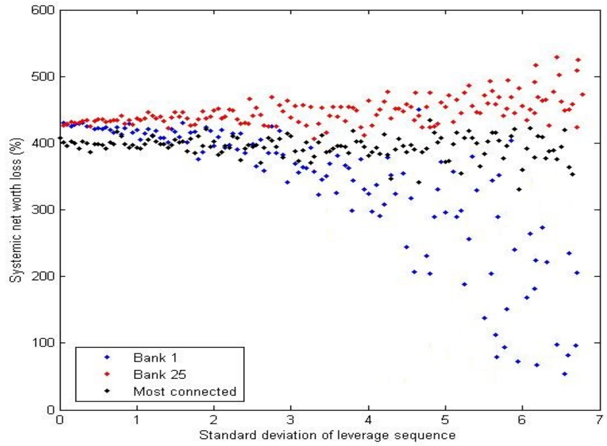
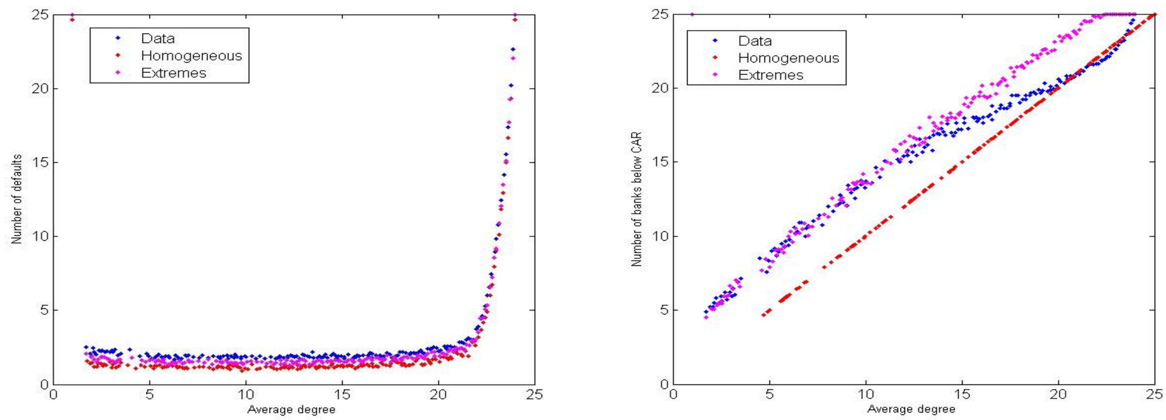


Fig. 12: Systemic % net worth loss

In addition to the data and homogeneous leverage sequence at the mean of the data, I introduce two extremely high and low leveraged banks to the homogeneous system.[17] For these three distributions, I aim to support the previous result that leverage asymmetry decreases resilience of the system. I introduce shocks to the most connected, the biggest borrowers and random banks.[18]

[17]Note that low and high leverage banks are added symmetrically around mean in order not to change overall strength of the system. I add +/- 1 standard deviations from the mean.Thus I keep overall level of capital same for the system. Note that case "extremes" in the following graphs means this case.

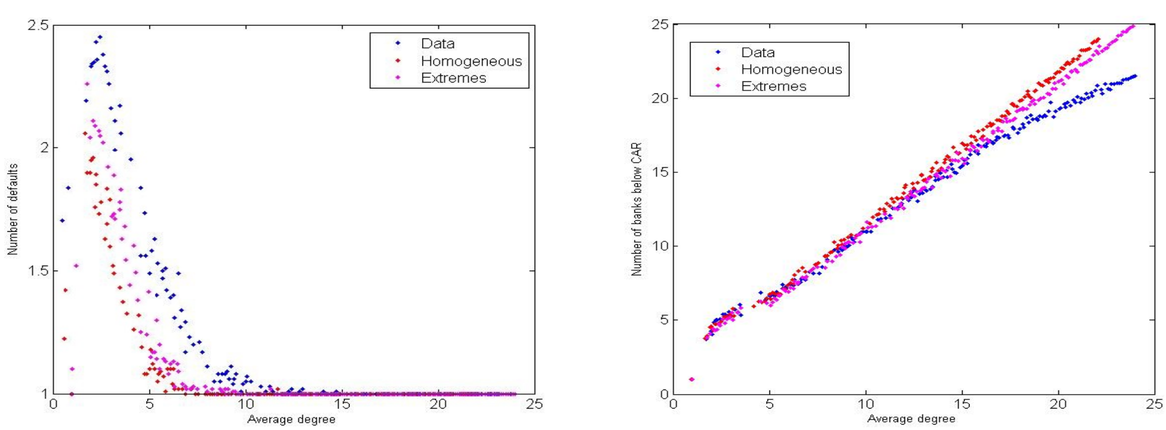
[18]In this experiment, the shock to the bank with the lowest leverage gives expected results, since it has the lowest leverage in the "extremes" sequence, when it receives the shock, the "extremes" sequence will be the one with minimum number of defaults, since I create and give shock to the strongest bank.



((a)) Defaults ((b)) Banks below CAR

Fig. 13: The most connected borrower

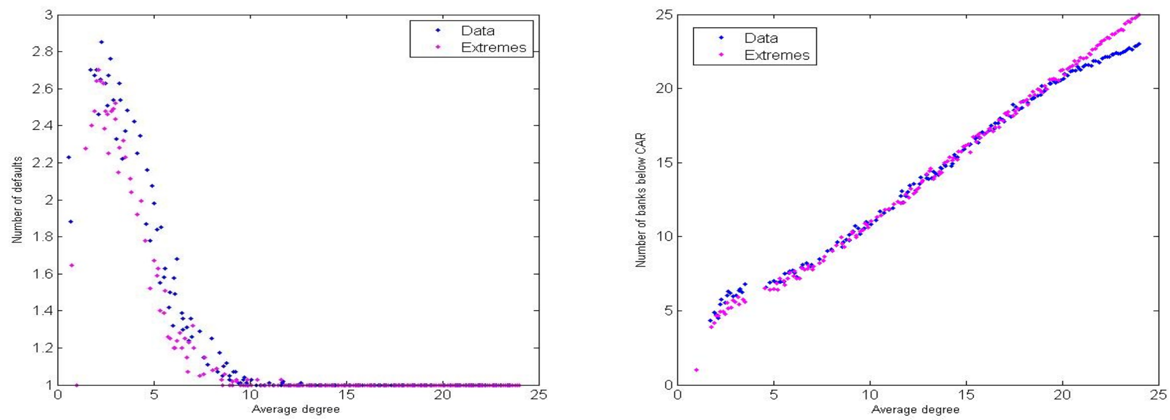
Figure 12(a) represent the result when the most connected borrower receives the shock in case of these three leverage distributions. For both measures, homogeneous distribution gives the best results in terms of the strength of the network. Adding two extremes makes system less resilient, and the more dispersed the leverages (i.e. data), the more vulnerable the system.



((a)) Defaults ((b)) Banks below CAR

Fig. 14: Random bank

Figure 13 illustrates the results with three sequence when the bank with the highest leverage receives the shock. The result of the most connected borrower case are still valid. The worst results is achieved by the data and the least number of defaults is received in the homogeneous case. The sequence with extreme banks gives the middle conseuences for both measures.



((a)) Defaults

((b)) Banks below CAR

Fig. 15: The biggest borrower

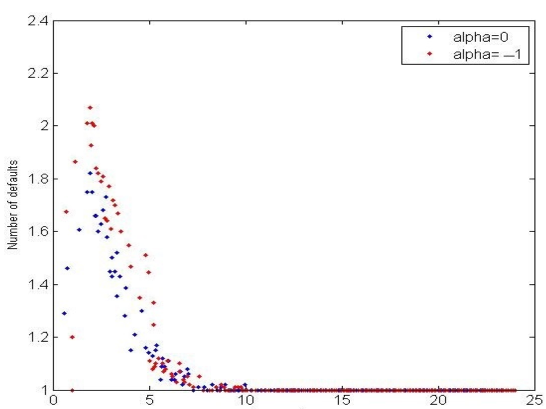
I introduce a shock to the biggest borrower in case of only data and “extremes” sequences, since I do not have a bigger borrower in homogeneous case. In this case, data again makes system more vulnerable than a relatively more equal distribution (i.e. “extremes”). Previous two results are valid in this case too.

3.8. Effect of Liquidity Channel

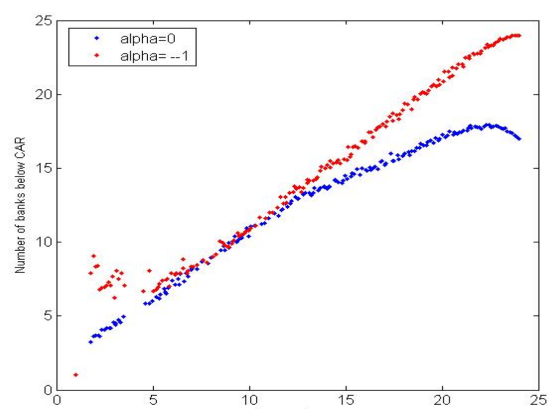
I also investigate the effect of liquidity on systemic risk in case of different targets of shocks. The aim is to see the difference in the impact of fire-sale when shock hits different target banks. Following Nier et al. (2007), I assume, when a bank defaults, its remaining assets are liquidated, however market fails to provide the liquidity to absorb these assets. In their model, price of assets is a decreasing function of the amount of assets needs to be liquidated. I use the inverse demand function for banks' assets as in Nier et al.:

$$P_r(x) = e^{\alpha x}$$

P_r represents the price of assets in the system at any round r after the shock hits, and α is a measure of limited liquidity of the asset market.[19] Following May and Arinaminpathy (2010), x is defined as percentage of the assets to be sold to all assets in the system. When there are no defaults, price of asset is equal to 1. If there is a default, $x > 0$, and thus $P_r < 1$. As a result, shock has an additional effect in the amount of $(1 - P_r)$ on the bank it hit. It also has an additional effect on all other banks, since value of their assets and their net worth decreases. Therefore, I expect to observe that results shift upward for all cases studied, since pricing effect makes all banks more vulnerable against shocks.[20] I examine the gap in the impacts of shock when the biggest and the smallest borrowers receive it. The results are provided in Figure 16 and 17.



((a)) Defaults



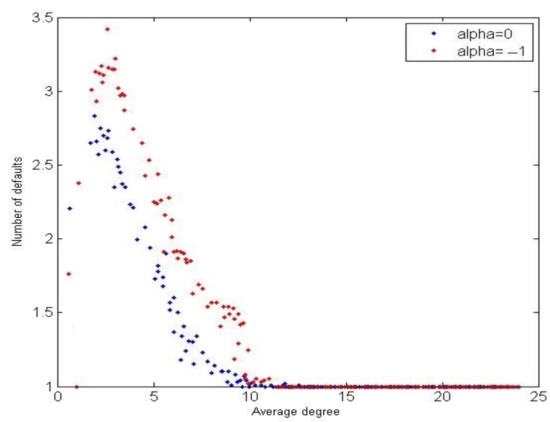
((b)) Banks below CAR

Fig. 16: The smallest borrower

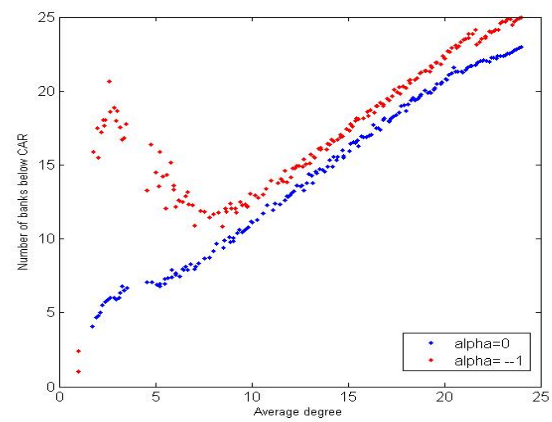
[19]When α is zero, there is no liquidity effect.

[20]I choose $\alpha = -1$ to introduce a liquidity channel, following Nier et al. in benchmark case. Note that, it is a dynamic pricing scheme. In each round, when further defaults occur and assets to be sold increases, the value of all assets remain in the system decreases.

Since liquidity channel introduces further endogenous and dynamic shocks to all banks, when the systemic impact of shock is higher due to higher first level contagion, the effect of liquidity is more clear. That is, when system is more vulnerable in the first round, it triggers higher endogenous shocks. It is also valid for number of banks below CAR. I infer that when the first level transmitted amount is higher, endogenous shocks arising from the liquidity channel during the stress period have more devastating consequences.



((a)) Defaults



((b)) Banks below CAR

Fig. 17: The biggest borrower

3.9. Policy Recommendations on Recent Banking Regulation

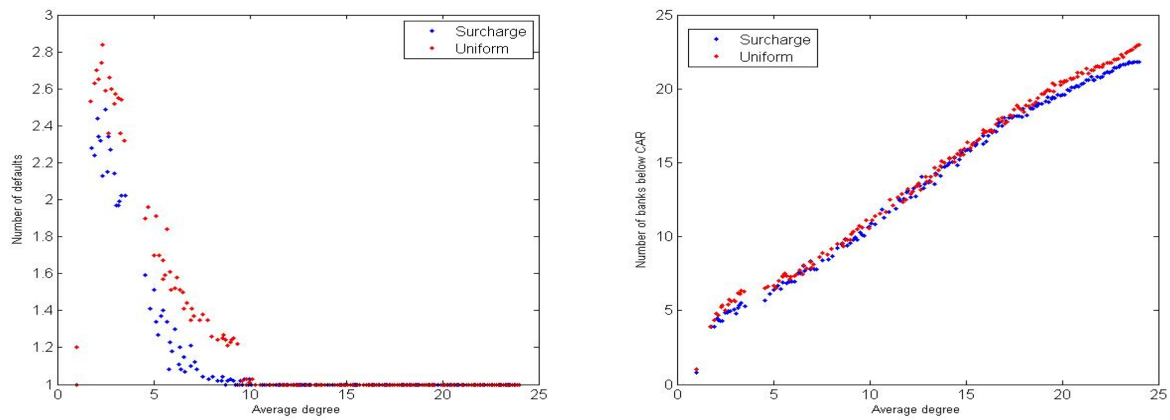
In November 2011, Financial Stability Board has made a critical framework change to reduce the risks posed by Global Systemically Important Financial Institutions (G-SIFIs). A following regulation[21] has altered the definition and requirements for the Global Systemically Important Banks (GSIB's).

[21]See http://www.bis.org/publ/bcbs201.pdf

Table 4: Additional Requirement

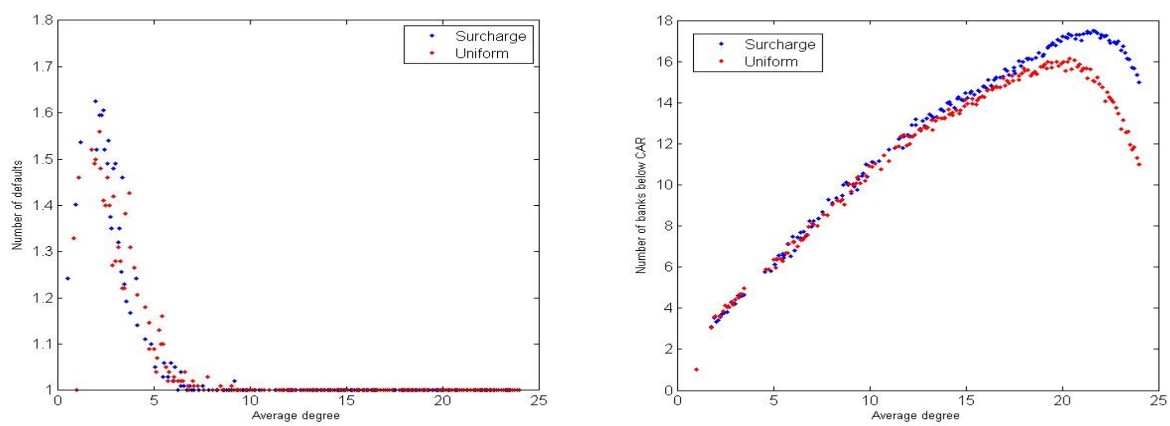
Bucket	Score Range	Minimum Additional Capital
5	D-	3.5%
4	C-D	2.5%
3	B-C	2.0%
2	A-B	1.5%
1	Cut-off point -A	1.0%

As stated by BIS, "The negative externalities associated with institutions that are perceived as not being allowed to fail due to their size, interconnectedness, complexity, lack of substitutability or global scope are well recognised". In order to mitigate the negative externalities that might arise from these global banks an additional capital surcharge will be implemented on these global banks. A bank is chosen as a GSIB on various criteria including the asset size and interconnectedness. Consequently, a bank which is chosen to be a GSIB will be required to hold an additional capital between 3.5% to 1%. As of November 2013, 29 Banks are qualified to be GSIB's. From a regulatory perspective, a high capital surcharge for a systemically important bank is expected to reduce the system-wide risk. Therefore, to verify whether the surcharge for the bank with highest leverage or asset size is an important task for the banking regulation. In the analysis, I wanted to see how much of the systemic risk can be reduced by using a surcharge to the GSIB's designed by the BASEL committee. Therefore, I have investigated the effectiveness of GSIB surcharge policy in the banking system. I have designed the banking network simulation analysis by applying the recent surcharge policy on the systemically important banks in the system. I have increased the capital adequacy by an additional 3.5% (a surcharge for the most risky class like BASEL), a 2.5% surcharge is applied for the 2^{nd} most leveraged bank, the 3^{rd} most levered bank's capital has been increased by 1.5% and finally for the 4^{th} most leveraged Bank 1% for the 5^{th} most leveraged bank.[22] I observe effectivenesses of two policy options in case of shocks to the smallest, the biggest and the most connected borrowers. Figure 17, 18 and 19 represent the result.



((a)) Defaults ((b)) Banks below CAR

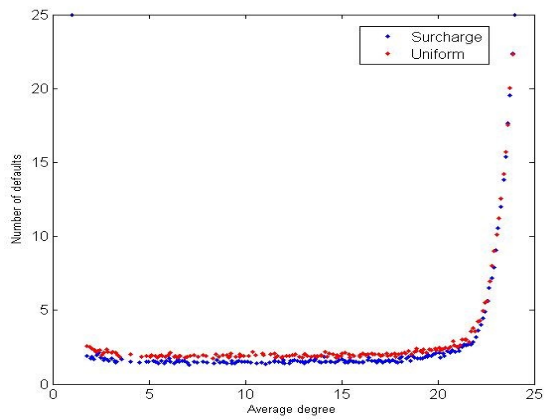
Fig. 18: The biggest borrower



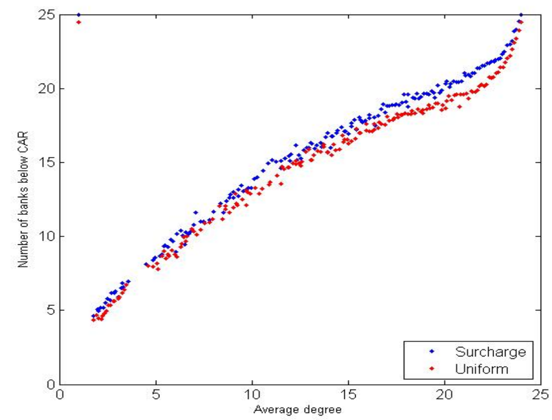
((a)) Defaults ((b)) Banks below CAR

Fig. 19: The smallest borrower

[22]System-wide increase in E is 525. Other policy option is to distribute this aggregate amount with 21 additional E_i's to all banks.



((a)) Defaults



((b)) Banks below CAR

Fig. 20: The most connected borrower

In the above graphs, the surcharge is applied for the most levered banks improves the health of banking system in general. I observe that same amount of capital injection with surcharge policy is more effective than a uniform capital increment for all banks. Especially when the most connected and the biggest borrowers receive shock, the result is clear. On the other side, if the smallest borrower is hit by the shock, the effectiveness of two options are not easy to identify. As can be seen, under normal conditions, the shock size and the bank number of defaults are positively correlated. However, as I add more capital for the levered bank the number of defaults reduce significantly. More specifically, it is more effective when the most levered banks is hit by the shock. That is because of the direct effect of its increased leverage when Bank 25 receives the shock. If Bank 1 faces with an equity shock, in the first step, surcharge is not effective since its leverage is kept same, but after the first round, while systemic impacts of the shock is spreading from borrowers to lenders via linkages, whenever one of the most levered 5 banks (the surcharged banks) is linked to banks that default, the effect of surcharge becomes apparent. On the other side, the effectiveness of surcharge is observable when the most connected borrowers receives the shock, since it is likely to be linked to one of the most levered 5 banks. In order to extend the scope of the experiment, I compare two regulatory capital strategies. First, I consider a surcharge policy where only the most levered banks will be asked to put aside a higher capital. In contrast, I assume a marginal increase in the required capital of each banks, thus the system as a whole is better capitalized with a uniform increase in the net worths of all banks. I compare its effectiveness with surcharge policy by keeping the total amount of capital injection same for the whole system. Since, surcharge policy creates an amount of additional capital, the system-wide regulation may distribute the same amount uniformly among each banks, and thus the only difference in these two is the how the same amount of additional capital is distributed in the system. I conclude that network resilience increase with surcharge policy when other policy alternative is a uniform injection using same capital amount in total.

CHAPTER 4

CONCLUSION

Financial leverage is one of the main culprit of the recent financial crises. Therefore, studying the effect of financial leverage in a banking system is a very crucial step in understanding systemic risk and banking crisis. I have investigated the impact of leverage heterogeneity a financial network system. The financial network simulations indicate that differences in leverage has sharply deteriorate the systemic risk measures. Introducing financial leverage in the banking system has caused many of the banks to fail to attain the minimum capital requirements. On the other hand, the default rate in the banking system has increased sharply with the existence more levered institutions in the system. These results are particularly important since central banks typically conduct their stress testing analysis without considering the interconnectedness and the effect of leverage among banks. I also wanted to apply this simulation methodology to test the impact of recent financial regulation on Global Systemically Important Banks (GSIB). The recent regulation aims to charge higher capital requirement for banks with higher asset size, leverage. I have made a simulation to test the general effectiveness of this new BASEL III requirements. By applying the same surcharges documented by the regulation we conducted a stress testing exercise. This analysis revealed the fact that additional capital requirement (i.e. surcharge of capital) for highly leveraged banks makes the banking system to be more resilient. In other words, an idiosyncratic shock hitting the banking sector will be better handled if banks with higher leverage is asked to hold higher capital. The results suggest that, stress testing without banking interactions and leverage differentials will understate the level of systemic risk hidden in the system. Network simulations should be a complementary tools in conducting stress testing. Comparing market based systemic risk measures with the network based measures is left for the future research.

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